

Learning Multi-Timescale Phase-Amplitude Dynamics for Human-to-Robot Transfer: Toward Real-to-Sim-to-Real

Anonymous CORL LSRW submission

Paper ID *****

Abstract

Motion generation across heterogeneous embodiments is a significant challenge in robotics. The Real-to-Sim-to-Real framework provides a promising paradigm for transferring human demonstrations to robotic systems. Trajectory-based imitation learning requires learning dynamical models, which corresponds to constructing simulation models of demonstrator dynamics [1]. The learned dynamical model guides the imitator to track the desired trajectory generated by the model, enabling motion imitation across different embodiments, such as human-to-robot dynamic motion transfer. Previous approaches, however, have struggled to handle multi-timescale dynamics, where slow steady motions coexist with fast transient dynamics.

Traditional motion models can handle dynamic behaviors composed of steady closed orbits, but it remains unclear whether transient dynamics can be reliably extracted from demonstration data. In other words, transient motion generation is essentially a generalization problem, since transient behavior determines the modification of trajectories from out-of-distribution states toward the desired demonstration state. Therefore, multi-timescale dynamical modeling and representation are common challenges not only for imitation learning but also for the broader Real-to-Sim-to-Real.

Our published paper [2], as shown in Fig. 1, introduced a novel variational inference approach for learning latent dynamical models, which explicitly represents transient and steady dynamics via phase-amplitude reduction, a special case of Koopman operators. The method decomposes the demonstrator’s behavior into transient and steady latent components, and enables the independent generation of both. The original work proposed the phase-amplitude-based imitation learning method and a latent state feedback framework to adapt the robot (imitator) behavior to the human (demonstrator) dynamical model. This framework allows multi-timescale comparison of demonstrator and imitator dynamics in latent space and improves the imitator’s ability to reproduce both the steady and transient behaviors of the demonstrator.

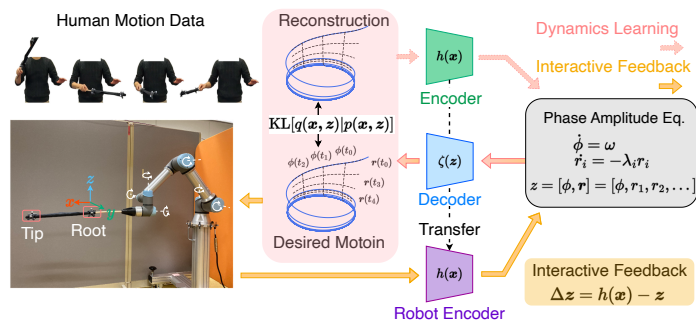


Figure 1. Phase-Amplitude-Based Imitation Learning

The contributions of our work are:

1. A variational inference-based dynamics learning approach that incorporates flexible graphical model-based loss function design and introduces an alternative likelihood-based loss function.
2. A phase-amplitude-based latent dynamical model that represents steady and transient behavior, together with a feedback system for tracking multi-timescale dynamics. The feedback system regenerates the "desired trajectory" for tracking the imitator and modifies its behavior.
3. A real-world human-to-robot transfer demonstration: the transfer of human baton-swinging motion to a robotic arm without adaptation using imitator data.

Our proposed model learning method is applicable not only to imitation learning but also to a wide range of heterogeneous-embodiment motion generation and the analysis of latent dynamical structures in robot agents. Demonstrator dynamics modeling enhances robustness and generalization by generating the desired trajectory for out-of-distribution behavior. Furthermore, phase-amplitude-based modeling can encode the imitator dynamics and apply the model within Sim2Real or model predictive control (MPC) frameworks. By integrating it with reinforcement learning and foundation models, it is expected to enable modeling and simulation of real-world data across multiple timescales.

066

References

067

[1] Yunhai Han, Mandy Xie, Ye Zhao, and Harish Ravichandar.

068

On the utility of koopman operator theory in learning dexter-

069

ous manipulation skills. In *Proceedings of the Conference on*

070

Robot Learning, pages 106–126, 2023. 1

071

[2] Satoshi Yamamori and Jun Morimoto. Phase-amplitude

072

reduction-based imitation learning. *Advanced Robotics*, 39

073

(3):156–170, 2024. [https://doi.org/10.1080/](https://doi.org/10.1080/01691864.2024.2441242)

074

[01691864.2024.2441242](https://doi.org/10.1080/01691864.2024.2441242). 1